Experimental AR Fault Detection Methods for a Hydraulic Robot

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Abstract

Robots in hazardous environments must meet stringent requirements of both durability and reliability to be safe, as robust systems and efficient reliability techniques are critical to safe operation in these environments. Rosie, a large hydraulic robot designed for nuclear reactor decontamination and dismantlement, is a prime example of such a robot. The study discussed here uses a hydraulic testbed which closely models Rosie's wheel actuators to gather data for development and testing of effective data analysis procedures aimed at reducing the dangers associated with dynamic failures this worksystem and others like it.

This paper focuses on practical use and theoretical elaboration of the analytical redundancy technique which is used to efficiently detect faults that have been determined to be mission-hazardous by previous FMECA and fault tree analyses of the Rosie system. We believe we have contributed significant improvements to the potential overall reliability of the system. Additionally, we have expanded the applicability of the AR method to nonlinear systems in the course of our work, making this valuable fault detection method more broadly applicable.

Introduction

One of the most important and fastest growing areas in the robotics industry is the development of robots capable of working in hazardous environments (refs. 1-4). Providing a high level of functionality in these arenas is important simply because humans cannot safely or cheaply work there. Additionally, system failures can cause serious collateral damage such as containment breaches, the environment can impede repair, and extracting damaged robots is often dangerous. Dynamic fault detection systems that monitor in real time, such as the analytical redundancy (AR) method described here, can contribute significantly to system reliability and safety, reducing these dangers. This allows completion of previously impossible tasks and often involves job creation rather than destruction. For these reasons, the University-based part of our team has investigated reliability issues for robots extensively (refs. 5-7). (The group consists of a collaboration of the Rice and Clemson based university groups with Foster-Miller Technologies Incorporated, an organization with considerable experience in evaluating the reliability of hydraulic systems.)

The Rosie mobile worksystem (refs. 8, 9) is an important and interesting example robot that is on the cutting edge of hazardous environment robotics, which has served as our inspiration and motivation for this work. Rosie, under development by RedZone Robotics Inc. and Carnegie Mellon University's Field Robotics Center, is a heavy-duty hydraulic robot designed for nuclear reactor decontamination and dismantlement. The robot has four independently steerable wheels powered by hydraulic motors supporting a chassis sporting a heavy-duty crane/manipulator. Fault detection for Rosie is interesting and important, and we are additionally using Rosie as a intermediate step to begin looking at fault detection for hydraulic systems in general.

Our work focused on a method known as *analytical redundancy* (refs. 7, 10), or AR. AR is a model-based state-space technique that derives the maximum number of independent tests of the consistency of sensor data with the linearized system model and past control inputs. AR yields tests to determine whether the system is performing normally, or is deviating from the nominal model and presumably under fault conditions. We have used this technique successfully on electrical robotic systems in the past (ref. 4), and is now applying it to the hydraulic Rosie-like systems.

In a previous paper (ref. 7), we discussed the derivation through AR of a suite of model based tests for the default sensor package for hydraulic wheel actuators, and introduced a system for using AR efficiently in nonlinear systems. Some of these tests are comparison of the actual system response to control inputs to the predicted response indicated by the model. The other tests uncovered by the AR analysis reflect higher order state interdependencies, as discussed later and in (ref. 7).

Rosie and the Hydraulic Testbed

Notation: The following variable names are used in this paper.

- A, B, and C are the canonical discrete time state space system matrices
- B_m is the viscous damping coefficient
- $C_{tm} = c_{em}+c_{im}$ represent total, external, and internal leakage, respectively
- d_m is the volumetric displacement of the motor
- J_t is the inertia of the motor and load
- K_f, k_q and k_c are valve flow coefficients
- $M = k_c+C_{tm}$ is a generalized pressure coefficient
- p_l and $p(k)$ are the continuous and discrete pressure drops across the motor
- p_s is the hydraulic power supply nominal pressure of 3000 PSI
- Q is the net fluid flow into the spool valve
- t is the continuous time variable, k the discrete time variable, Δt is the time step
- T_g is the torque generated by the motor
- T_l is the load torque
- *V1* and *V2* are linear AR tests, *NV3* and *NV4* are nonlinear tests
- v_t is the volume of fluid within the motor
- u_v and $u(k)$ are the servovalve position
- $\underline{x}(k)$ is the state vector
- β_e is the bulk modulus of the hydraulic fluid
- θ_m and $\theta(k)$ are the position of the motor shaft
- ρ is the hydraulic fluid density

The Testbed: The hydraulic wheel actuator subsystem has been determined to be a vital component of the mobile platform through FMECA and fault tree based reliability analysis. A failure of a wheel mechanism may prevent the removal of the chassis from the reactor work site, which may be hazardous to potential repairmen. The goal of the project was to develop effective data analysis procedures for hydraulic wheel actuators and implement them on a testbed system under construction at Foster-Miller. The results of this project can then be used to enhance the reliability of existing and future robots.

The system we are considering consists of a rotary hydraulic motor connected to a 3000 PSI hydraulic power supply through a hydraulic spool valve, as seen in figure 1. This system has considerable advantages as an actuator in a nuclear environment. Hydraulic systems are rugged and powerful, and much less likely to produce dangerous sparks than an electrical system. However, hydraulic systems are vulnerable to many faults that electrical systems do not experience, and are much harder to model due to their inherently nonlinear nature.

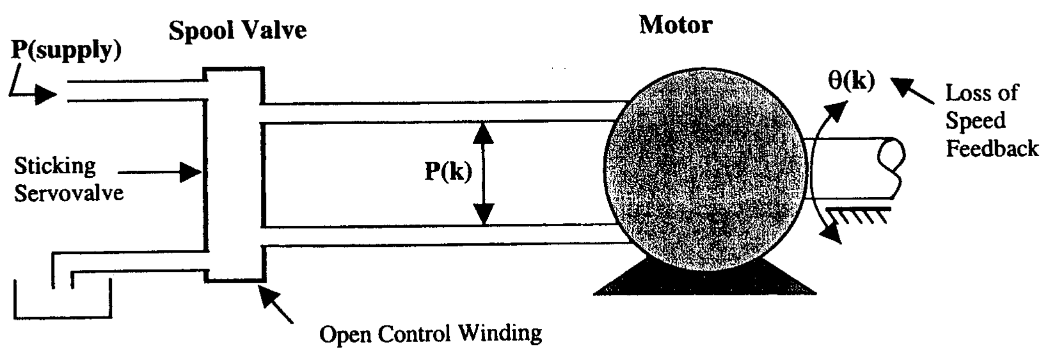

Figure 1. Hydraulic System Testbed

The dynamic equations for modeling this system are equations (1) and (2) (ref. 11):

$$T_g = p_l d_m = J_t \ddot{\theta}_m + B_m \dot{\theta}_m + T_l, \quad (1)$$

$$Q = u_v K_f \sqrt{\tfrac{2}{\rho}(p_s - p_l)} = d_m \dot{\theta}_m + (c_{im} + c_{em}) p_l + \frac{v_t \dot{p}_l}{4\beta_e} \quad (2)$$

Analytical Redundancy: The analytical redundancy (AR) method allows us to explicitly derive the maximum possible number of linearly independent consistency tests for a system (refs. 4, 10). Using a state-space control model of the system of interest, AR exploits the null space of the observability matrix to allow the creation of a set of test equations. These tests use sensor data histories and known past control inputs to detect any deviation whatsoever from the static or dynamic behaviors of the model. The deviations can then be analyzed for signs that indicate specific faults within the system.

The core of AR is the equation (3) (ref. 10), which is used to determine the systems' observability null space:

$$[\Omega] \begin{bmatrix} \textit{Observability} \\ \textit{Matrix} \end{bmatrix} \underline{u}(k) = \mathbf{0}. \quad (3)$$

The null space of Ω represents the space the system state vector should operate in if functioning correctly. Since most systems will be somewhat noisy and possibly inaccurately modeled, it is likely that the state vector will project slightly out of the Ω space. Our research has allowed us to reduce these errors by explicitly modeling the nonlinearity of the system, as discussed in previous paper (refs. 7, 12).

Using the equations (1) and (2) to model our testbed and our new nonlinear AR techniques from (ref. 12), we can derive the modified AR tests given in equations (4) through (7):

$$V1 = \frac{B_m \Delta t - J_t}{J_t} \dot{\theta}(k) + \dot{\theta}(k+1) + \frac{-d_m \Delta t}{J_t} p(k) = 0, \quad (4)$$

$$V2 = \left(-1 + \frac{2B_m \Delta t}{J_t} + \frac{-B_m^2 \Delta t^2}{J_t^2} + \frac{4\beta d_m^2 \Delta t^2}{J_t v_t} \right) \dot{\theta}(k) + \left(\frac{d_m B_m \Delta t^2}{J_t^2} + \frac{-2d_m \Delta t}{J_t} + \frac{4\beta_e d_m M \Delta t^2}{J_t v_t} \right) p(k) + \dot{\theta}(k+2) + \left(\frac{-4\beta d_m k_q \Delta t^2}{J_t v_t} \right) u(k) = 0, \quad (5)$$

$$NV3 = \frac{4\beta_e d_m \Delta t}{v_t} \dot{\theta}(k) + \frac{4\beta_e C_{tm} \Delta t - v_t}{v_t} p(k) + p(k+1) + \frac{-4\beta_e k_q \Delta t}{v_t \sqrt{p_s}} u(k) \left(\sqrt{(p_s - p(k))} \right) = 0, \quad (6)$$

$$NV4 = \left(\frac{4\beta_e d_m \Delta t}{v_t} \right) \left(\dot{\theta}(k+1) - \dot{\theta}(k) \right) + p(k+2) + \left(-2 + \frac{4\beta_e C_{tm} \Delta t}{v_t} \right) p(k+1) + \left(1 - \frac{4\beta_e C_{tm} \Delta t}{v_t} \right) p(k) + \left(\frac{-4\beta_e k_q \Delta t}{v_t \sqrt{p_s}} \right) \left(u(k+1) - u(k) \right) \sqrt{(p_s - p(k))} + \left(\frac{4\beta_e k_q \Delta t}{v_t \sqrt{p_s}} \right) u(k) \frac{(p(k+1) - p(k))}{\sqrt{(p_s - p(k))}} = 0. \quad (7)$$

The AR tests used can be interpreted as follows:

V1: A discretized version of the linear differential equation describing the physical dynamics of the motor and load and their relation to the pressure load across the motor. This test checks to make sure that the motor is working as expected.

The faults investigated tended to cause large spikes in the output from this test. Since none of these faults caused large permanent changes in the characteristics of the motor, this is not surprising. The onset of the fault disturbs the entire system, momentarily causing a large fault signal. Once the disturbance settles, the undamaged motor resumes behaving as expected.

V2: This test is in some sense the discrete time derivative of equation V1. However, it is also a blending of the hydraulic equation with the kinematic equation, so its behavior is not immediately predictable as derivative-like. Further analysis tells us that this equation can react to faults in ways that V1 cannot.

V2 results are harder to examine than V1's since, as can be seen in the data section, V2's output does not center on zero. It gives a steady-state value representing unmodeled system and load effects. Thus the test responds to changes in system parameters by outputting a step function as these values change.

As a consequence of this, V2 is not a good test for certain faults when the system parameters have changed for other reasons. For example, minor changes in system parameters caused by the work needed to install a simulated fault can and do change the steady-state value of this test.

In the data analysis, this results in a difference bias between the V2 test result for the faulty run and the one for a fault free rig-configuration run with the nominal system parameters, even if the fault itself is not responsible for the bias change. This effect is misleading, but not at all problematic if understood. Small variations in the steady-state values of this test may be safely ignored, and the test is still useful for fault detection, as sudden steps in this test represent the occurrence of a fault. Such steps are not ambiguous.

NV3: This test is a discretized version of the equations representing the hydraulic characteristics of the servovalve and motor. NV3 examines the pressure and shaft position signals and determines if these are consistent with its model of the hydraulic system.

NV3 responds to faults with a step function, much like test V2. This makes it vulnerable to all the problems with varying system parameters that V2 has. (See above.) It is thus important to remember that a small steady-state difference between the faulty and rig configuration versions of this test is not necessarily significant.

NV4: NV4 is the "derivative" of NV3 in the same manner that V2 is the derivative of V1. It also blends the kinematic equation into the hydraulic one in a similar way to how V2 blends the hydraulic equation into the kinematic. In this case, the original equation exhibits the step function behavior, while the derivative, NV4, responds to faults with spikes similar to test V1.

A note about the y-axis of AR tests:

The y-axes of AR tests are arbitrary, as the test derivation algorithm is insensitive to multiplication through by a constant. The shape of the curve is important, its magnitude is not, as long as the scaling factor is constant between different runs of the same test. We were careful to insure that this restriction was followed for our tests. Thus, we should ignore units and magnitudes on the AR data plots presented below, concentrating instead exclusively on curve shape.

Results

In this section we examine example plots for a typical data run for various faults, and discuss the effectiveness of AR as a fault detection tool for each. The run with the fault installed is solid black, a fault free rig configuration run for comparison is gray and dotted. Dashed circles highlight areas of interest.

Figure 2 displays the results of the first fault of interest, which results from an open winding in the control servovalve. The onset and duration of this fault is clear in all AR tests. The open winding acts like a step input that is not accounted for in the model, provoking a strong AR response.

The next fault data, shown in figure 3, is from a sticking wheel motor control valve. As a ramp input is run through the controller, the valve periodically sticks in its current position. This is evident on all AR tests, although V1 and NV4 show clearest results. Included for comparison is raw data from the sensor that showed the clearest unprocessed reaction to the fault. Clearly, AR greatly amplified and isolated the fault signal. During the parts of the run where the system is stuck, it does not follow the dynamic model at all, and is thus easy to detect.

Figure 4 shows data from a loss of speed feedback in the servovalve fault. As the failed sensor invalidates the control loop, AR detects this as a deviation from the model-expected behavior. Note that AR does have some problem detecting this fault in an a idling system (not

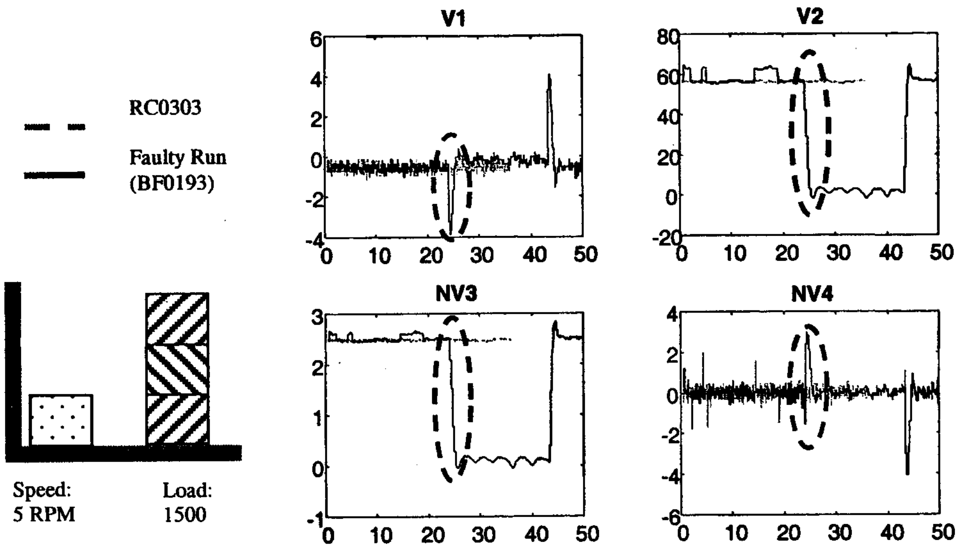

Figure 2. Open Winding Fault

shown). As the idling system is already giving a near-zero value for the zeroed out sensor, there is no deviation from the model, so the fault is undetectable by any model-based method until the expected output from the sensor deviates from the faulty stuck value. Despite this limitation, AR *would* alert the user as soon as a motion was attempted.

As seen above, the nonlinear AR-based methods proved very effective in detecting a significant number of real faults introduced into the hardware. We believe that development and careful investigation of faults induced in the Foster-Miller test rig has been very valuable, both in demonstrating that the AR theory "works" on real hardware, and in identifying areas in which alternative sensing strategies and/or fault detection techniques may be needed. The results clearly show that our AR framework is a useful and effective method of fault detection for hydraulic robot systems.

However, as AR is model based, and thus must deal with certain limits inherent in model based detection. A good example from our tests would

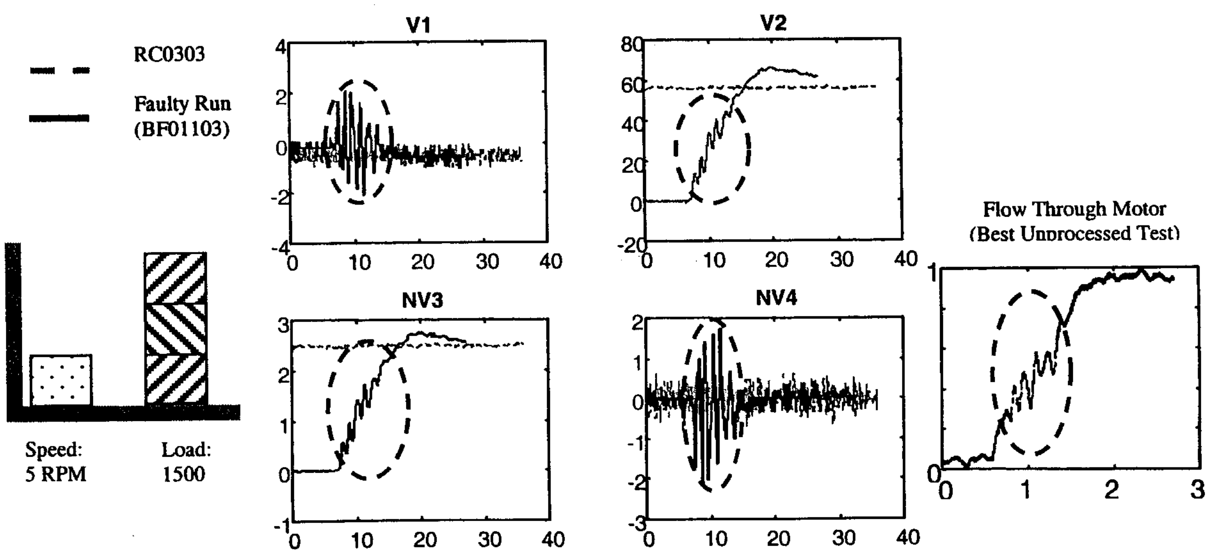

Figure 3. Sticking Servovalve Fault

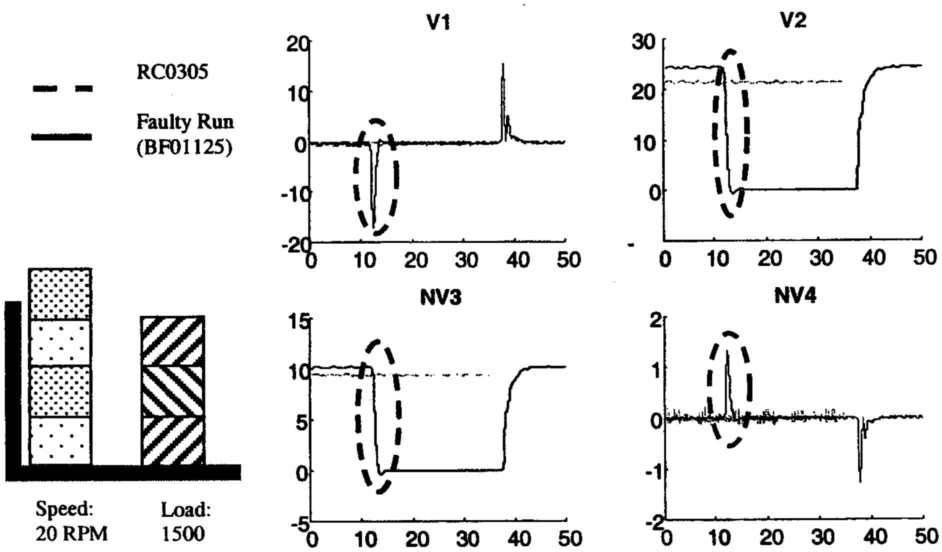

Figure 4. Loss of Speed Feedback Fault

be small leak faults. Leaks of a magnitude of 5% of the total flow is barely detectable by this system, and leaks of 1% or smaller are not detectable at all, as the variation from the model parameters is smaller than system noise. Even small leaks in high-pressure hydraulic systems are very serious faults, and detecting them is a priority. Thus AR is best used with complementary error detection schemes (such as spectral analysis) designed to detect faults that do not seriously affect parameters of the hydraulic dynamics, if such faults are likely to be a problem.

Conclusions and Future Work

AR fault detection is an appropriate monitoring method for hydraulic systems such as Rosie that must operate in hazardous environments. Safety and reliability are critical for success of these operations, and this work represents the first detailed examination, to our knowledge, of AR fault detection for these types of hydraulic robot systems. Better fault detection for hydraulics will reduce the costs associated with failures of such systems in the workplace by minimizing damage done by and to faulty systems as well as the amount of time wasted by false alarms.

Previous theory for rigorous model-based fault detection methods such as AR have been limited to linear systems, which is not appropriate for hydraulically driven robots. The nonlinear AR methods as developed here are of considerable theoretical interest while being directly applicable to the fault-detection for any significantly nonlinear system. The Rice and Clemson group is engaged in ongoing work to further develop theoretically robust nonlinear AR techniques.

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